Fusion of Content and Context in Human Language Technology

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National Security Agency
Fort Meade, Maryland

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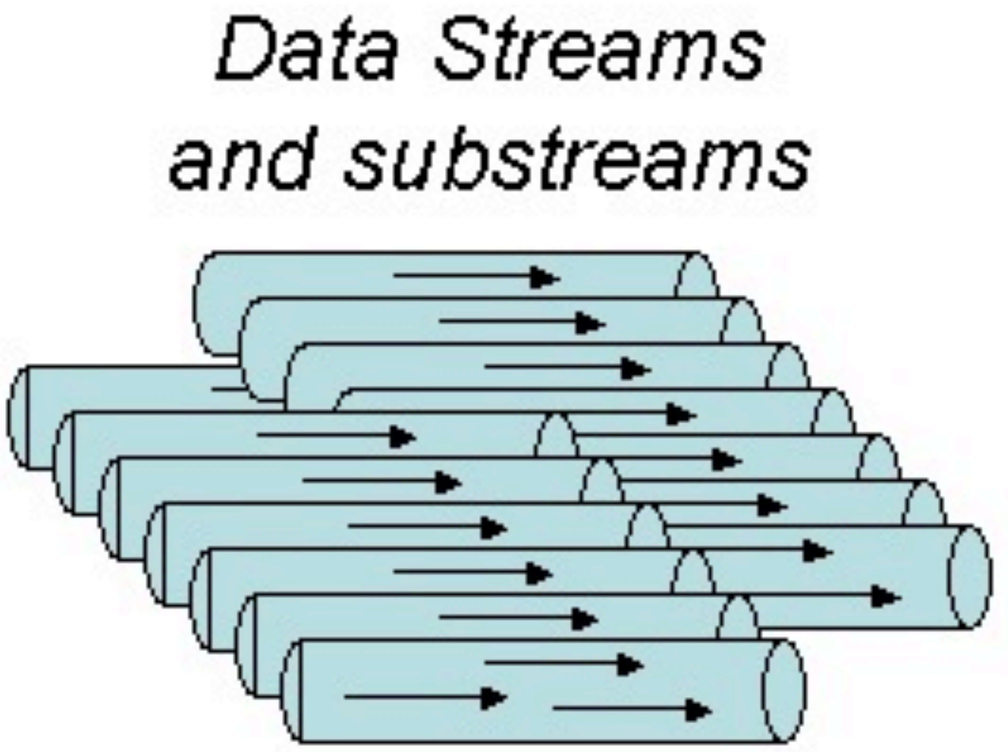
Outline

- Motivation: Coping with Information Overload
- Examples of Context and Content
- Random Attributed Graphs
- Three Tasks
  - Stream Characterization
  - *Vertex Nomination*
  - Dyadic Priors

Coping with Information Overload



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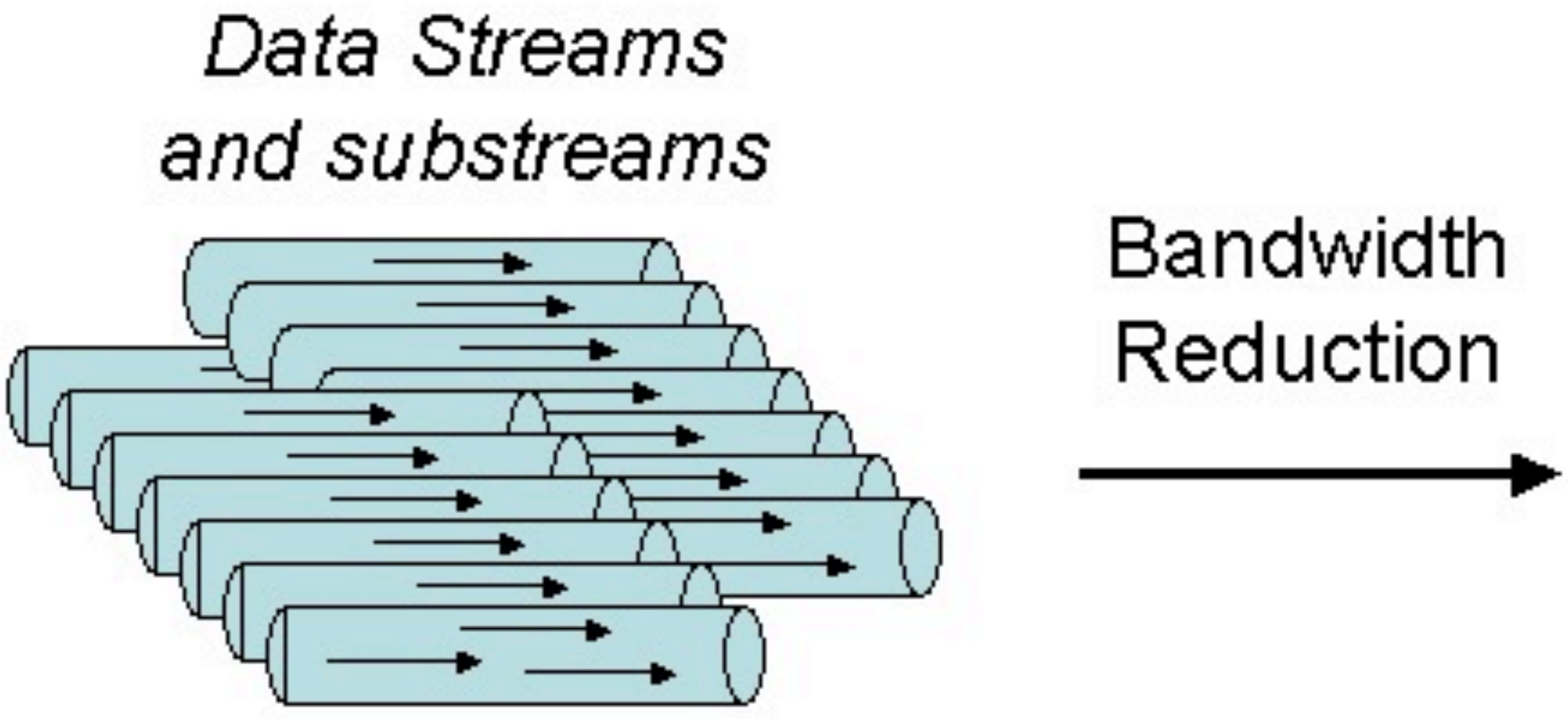

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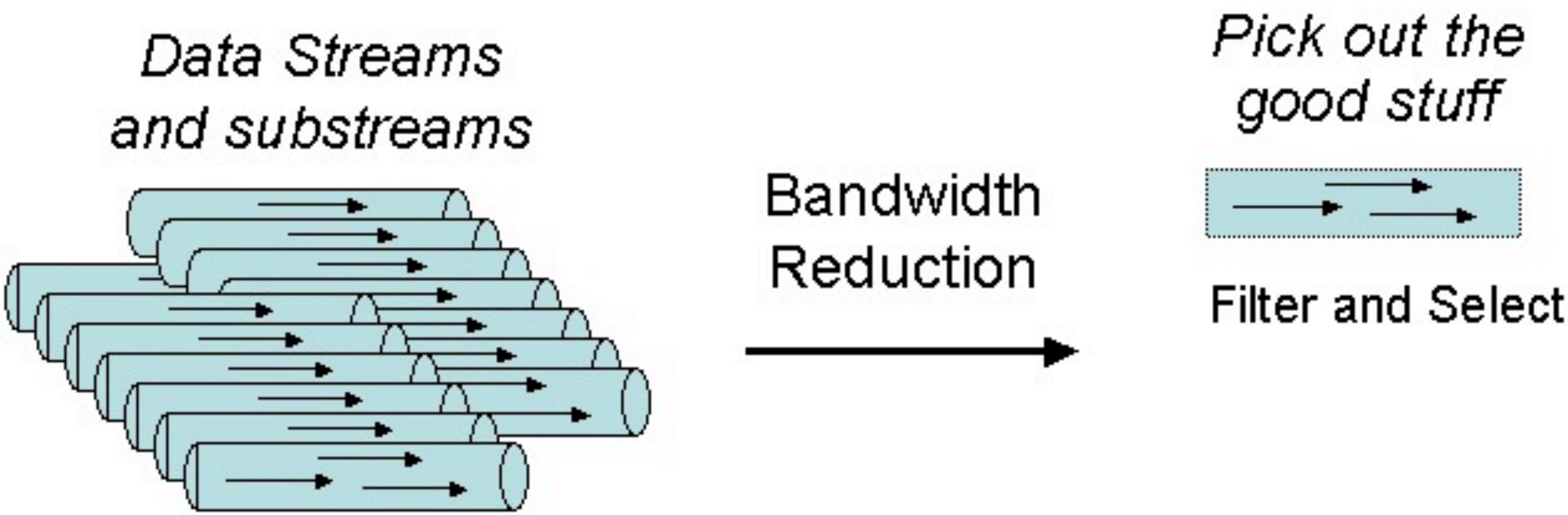

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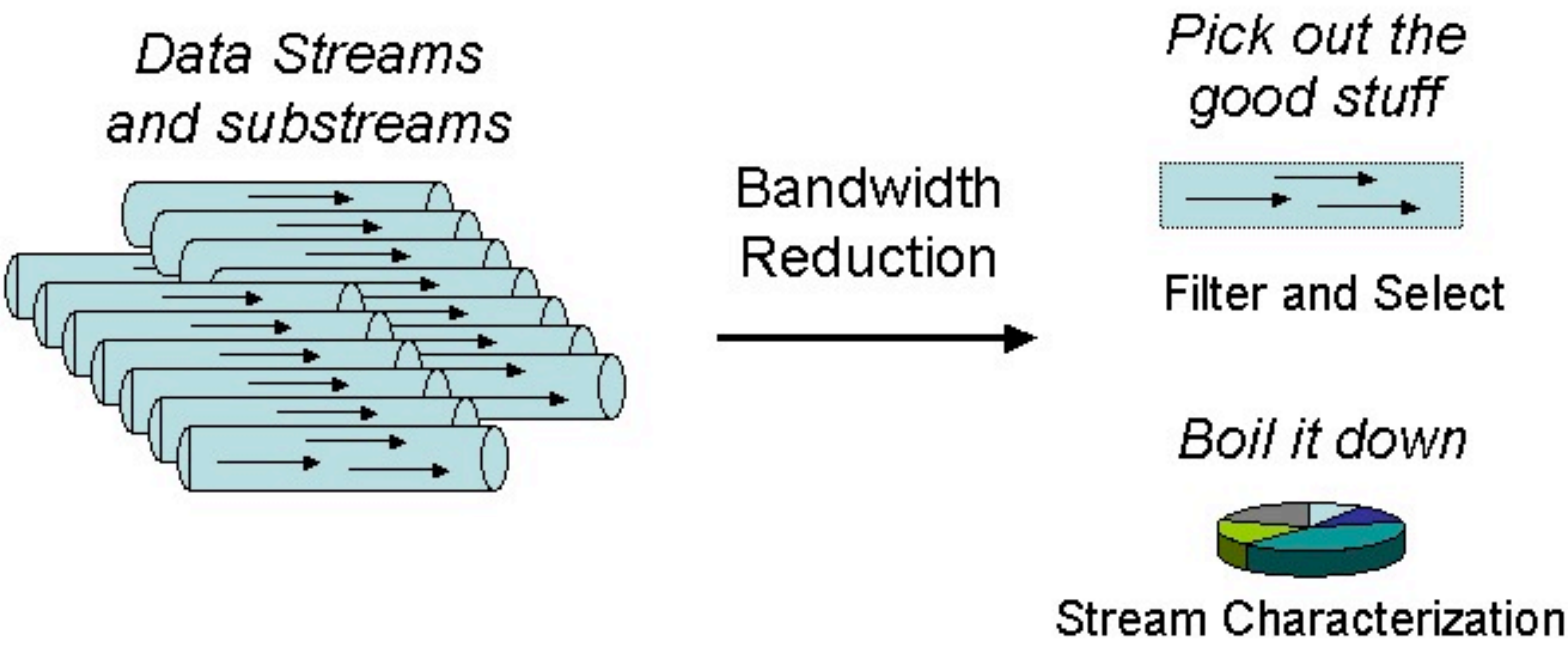

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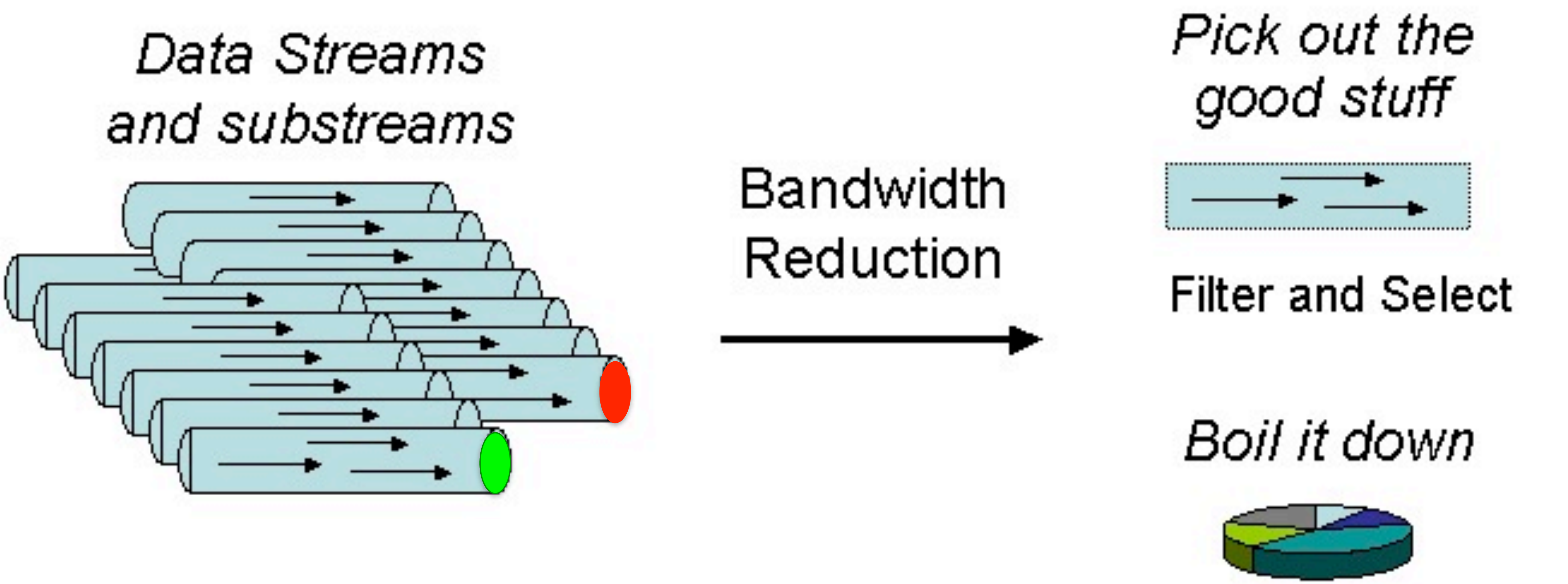

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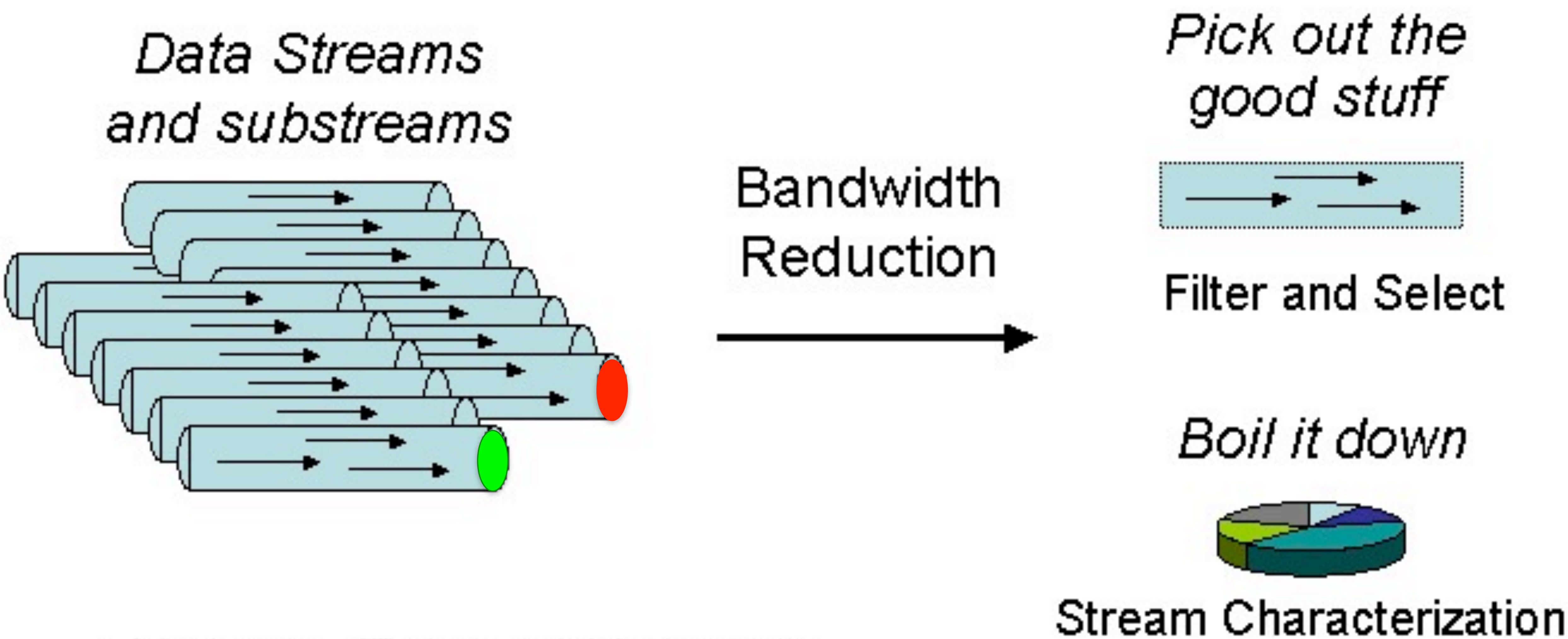
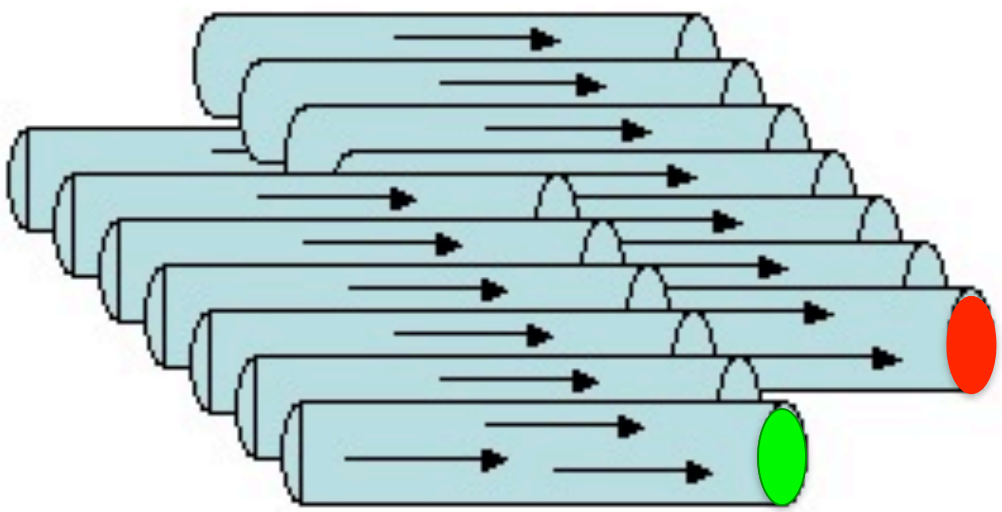


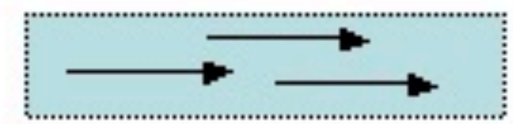
- Mature: External Metadata

Coping with Information Overload



Bandwidth
Reduction

Pick out the
good stuff



Filter and Select

Boil it down

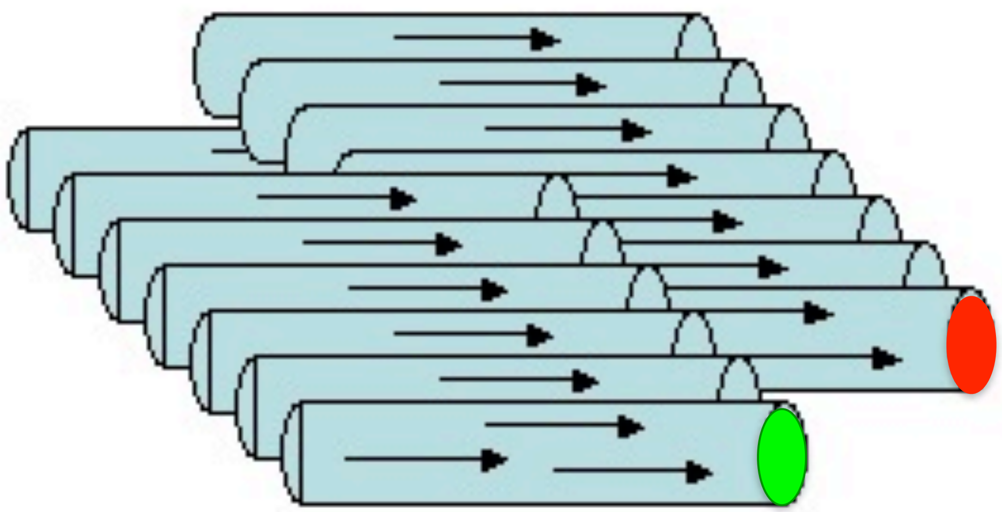
Stream Characterization

- Mature: External Metadata

- **Emerging: Metacontent**

Coping with Information Overload

Data Streams
and substreams



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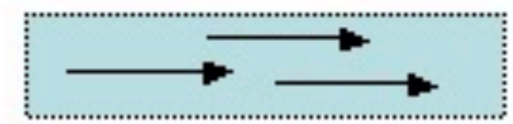

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Stream Characterization

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- **Emerging: Metacontent**

- ➢ *language*
- ➢ *speaker*
- ➢ *topic*

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challenge: how to exploit?

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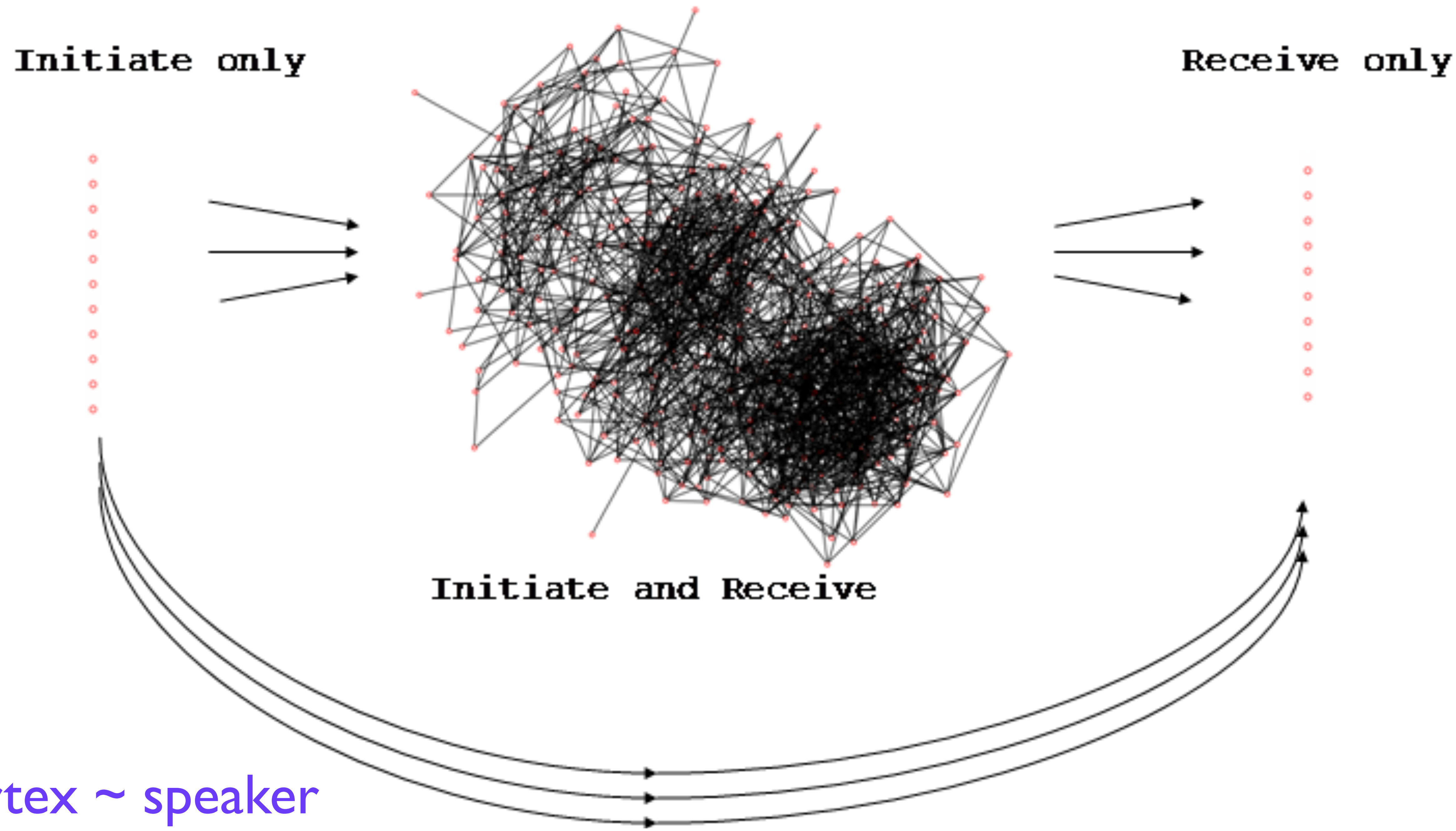
- Citeseer scientific articles have authors and citations

Communication Events from the Enron Corpus

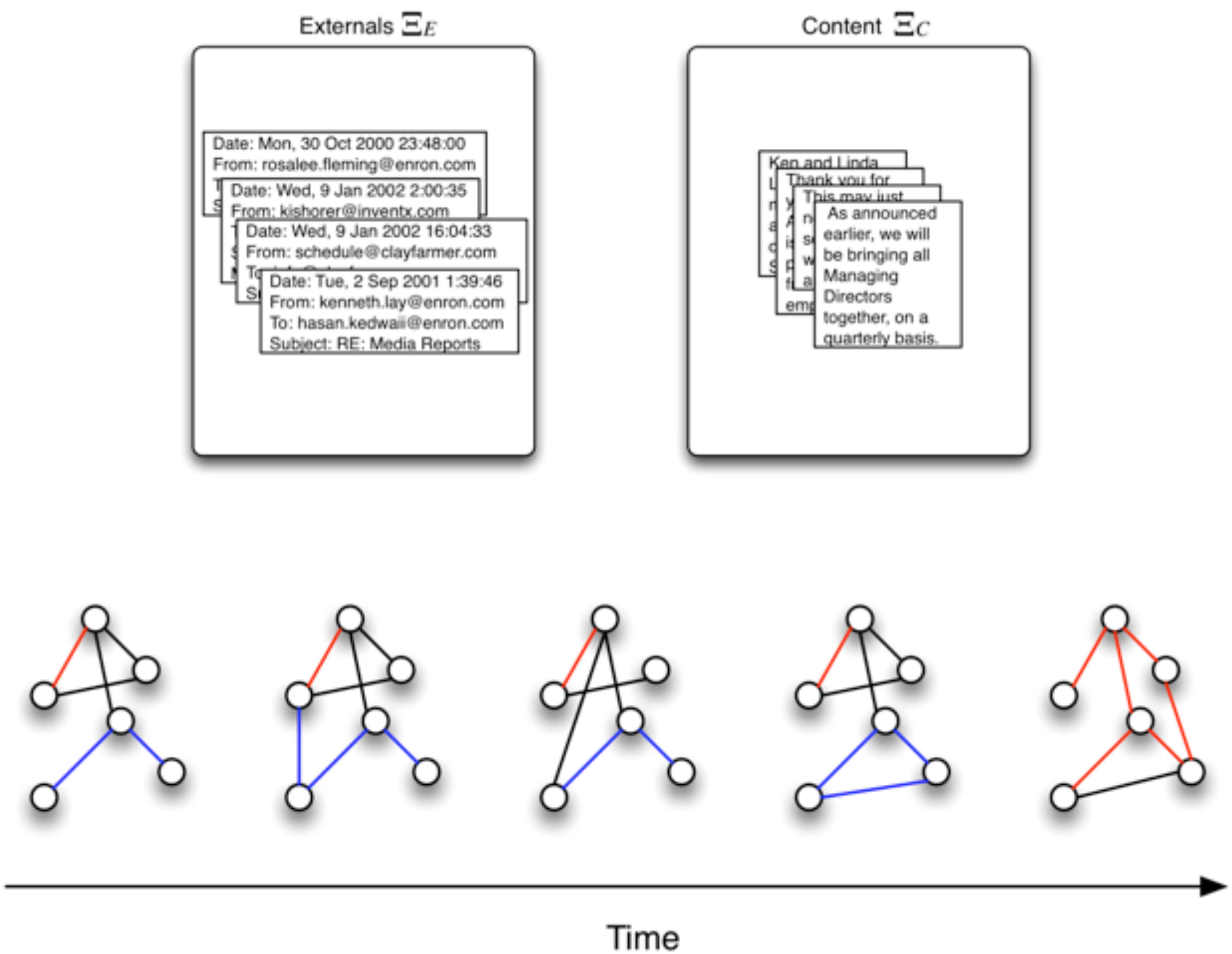
Date	Time	Sender	Receiver	Sender's Rank	Topic
2001-01-02	04:15:00	steven.k	jeff.d	Vice President	(1) California Analysis
2001-02-09	13:49:09	louise.k	andy.z	President	(9) Daily Business
2001-02-16	21:06:00	drew.f	jeff.d	Vice President	(5) California Enron
2001-02-26	22:30:00	james.s	john.l	Vice President	(14) Energy Newsfeed
2001-03-01	07:54:00	diana.s	kate.s	Trader	(5) California Enron
2001-04-06	05:15:00	mike.g	john.l	Manager	(7) Newsfeed California
2001-04-16	06:12:00	richard.s	steven.k	Vice President	(9) Daily Business
2001-05-11	16:02:00	andy.z	john.l	Vice President	(11) Enron Online
2001-06-27	17:44:24	s..s	geoff.s	Vice President	(9) Daily Business
2001-09-05	14:36:53	geoff.s	louise.k	Director	(12) Enrononline Daily
2001-09-15	20:51:20	m..p	louise.k	Vice President	(12) Enrononline Daily
2001-10-04	14:19:16	john.l	louise.k	CEO	(11) Enron Online
2001-10-05	18:49:05	j..k	richard.s	Vice President	(9) Daily Business
2001-10-08	17:50:19	shelley.c	darrell.s	Vice President	(1) California Analysis

SwitchBoard Communications Graph



Vertex ~ speaker
Edge ~ dialog

Time Series of Attributed Graphs



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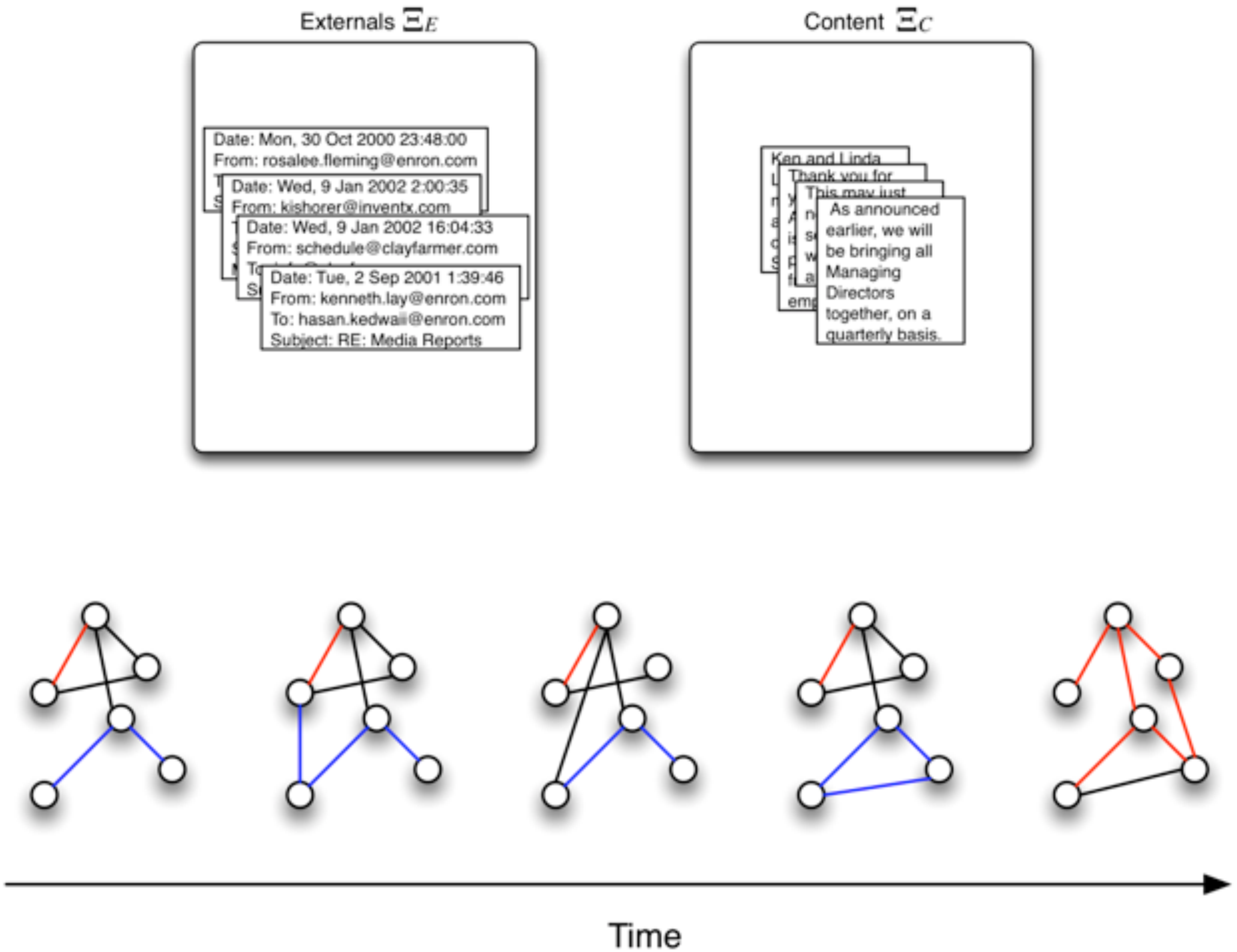

Generated by some random process $\mathbf{G}_t$?

Random Attributed Graphs (RAGs)

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- There is a computer science literature on attributed graphs, e.g. as produced by entity and relations, ignoring stochastic modeling.
- Before this research effort, *no* literature that we know of addressing time series of random attributed graphs.

Generative Models for RAGs

- Build RAG models by extending random graph models
- Erdos-Renyi (binomial) graphs, where a pair of vertices is connected with *iid* probability *p*.
- Kidney/Egg models, Block models
- Latent Position and Random Dot Product Models where

$$p_{ij} = h(x_i , x_j)$$

- Construct from time series of communication events

$$M = \{ (t, u_t , v_t , s_t) \}_t$$

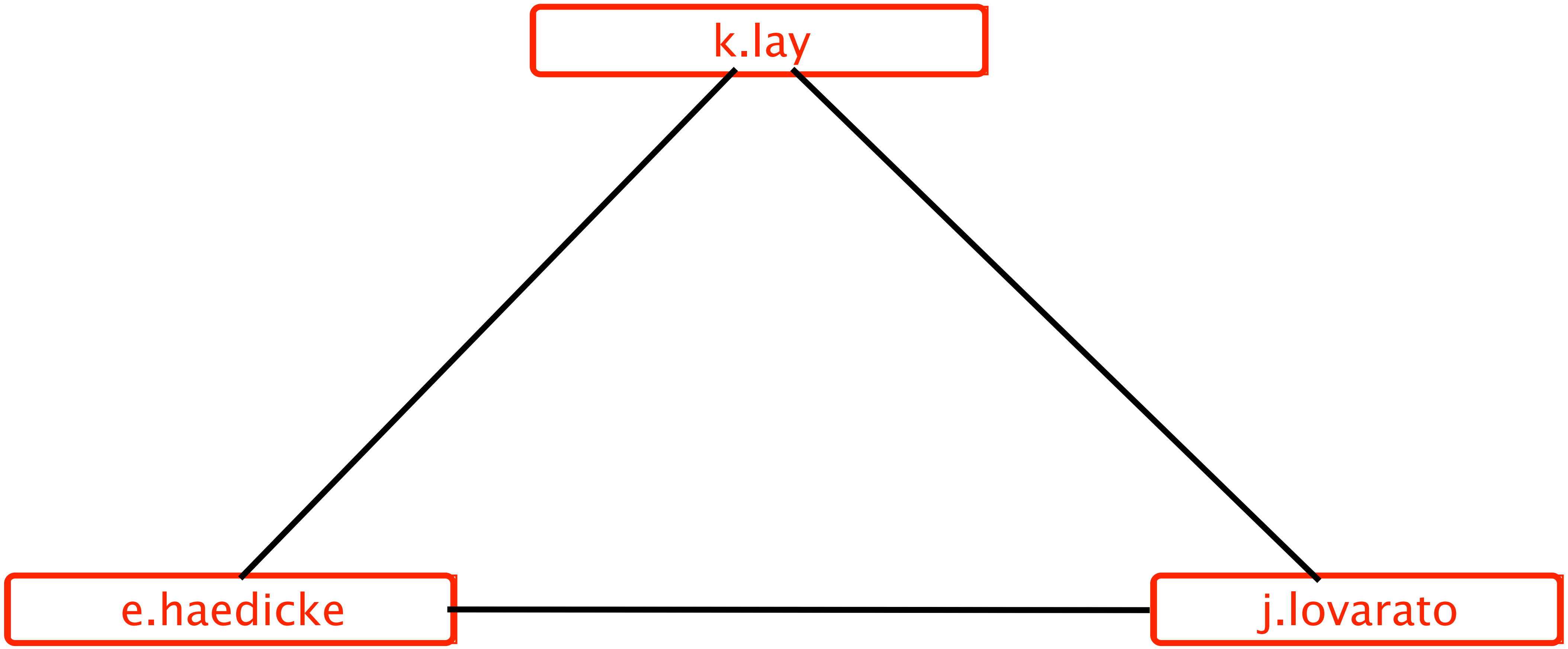
Vertex Nomination

- Cf. fraud and social network analysis
  - significant literature using graphs
- Intuition for fusion is clear
- Experimental evaluation on Enron email corpus
- Summer workshop
  - at JHU Human Language Technology COE
  - participants from all over the U.S.

Experimental Methodology

- Given a set of red vertices
- Occlude subset of red vertices
- Develop method for nominating vertices as red
- Evaluate on how well it discovers those occluded *red* vertices
  - versus false nominations

Enron Example: Red Vertices -> Red Documents



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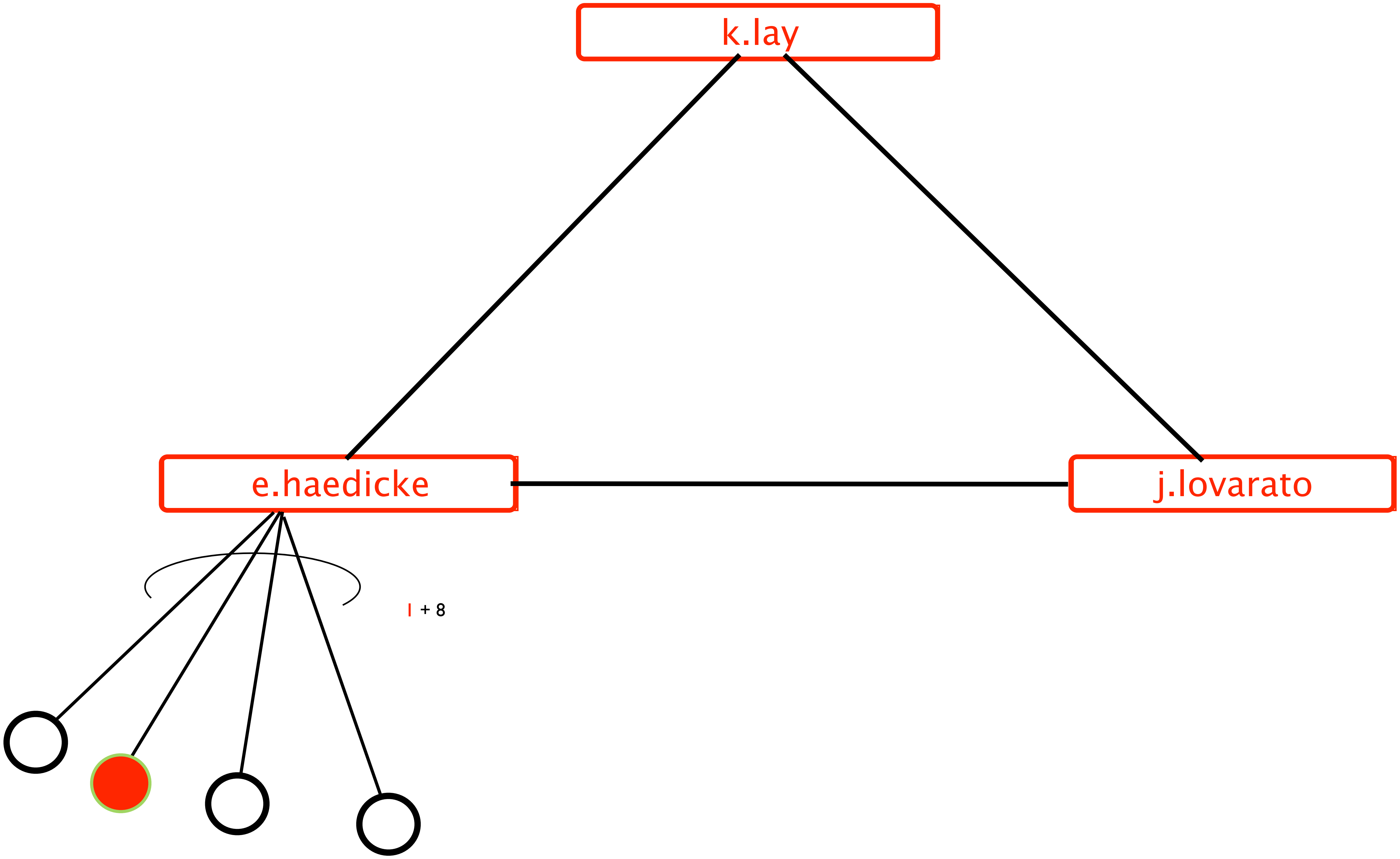

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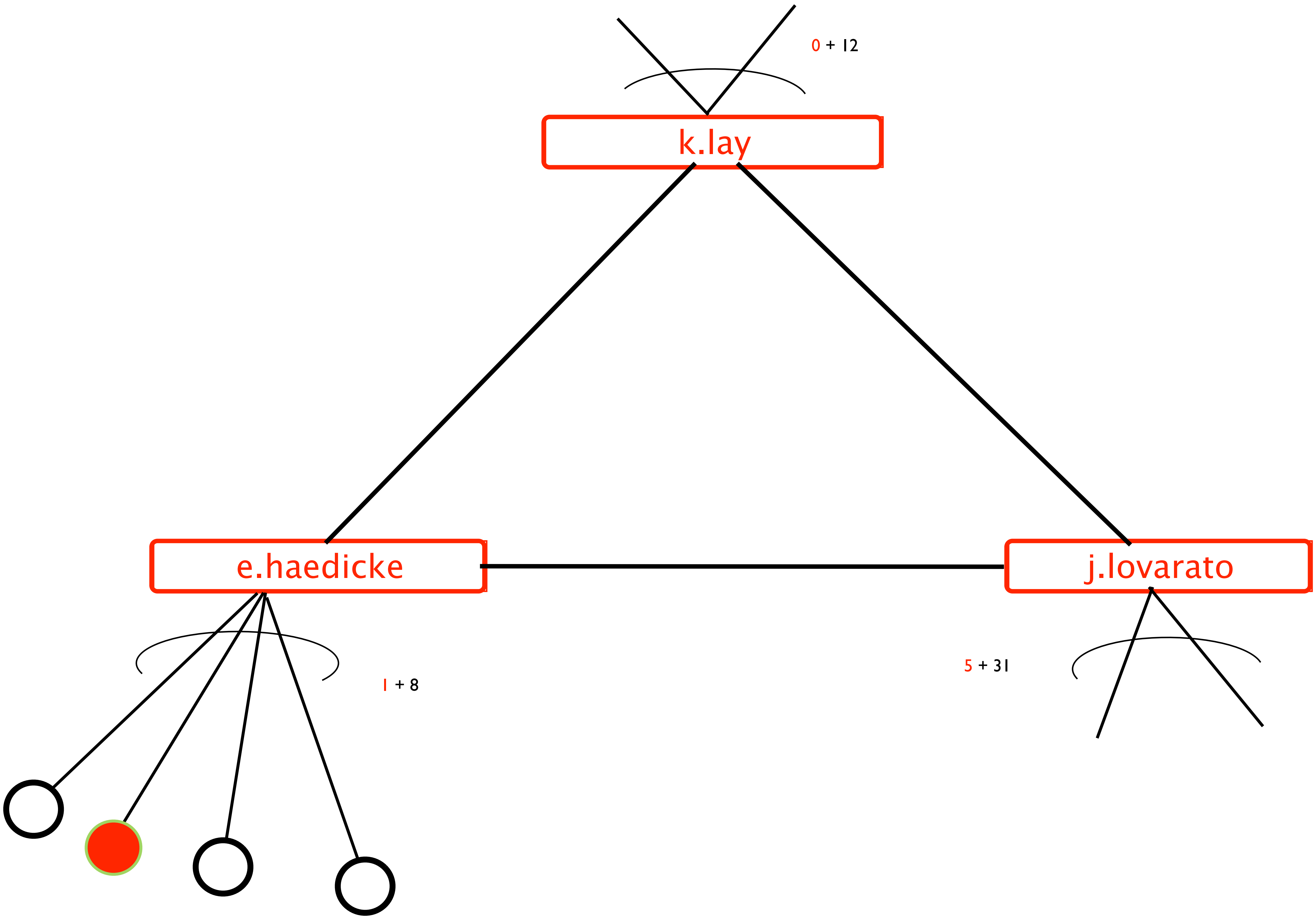

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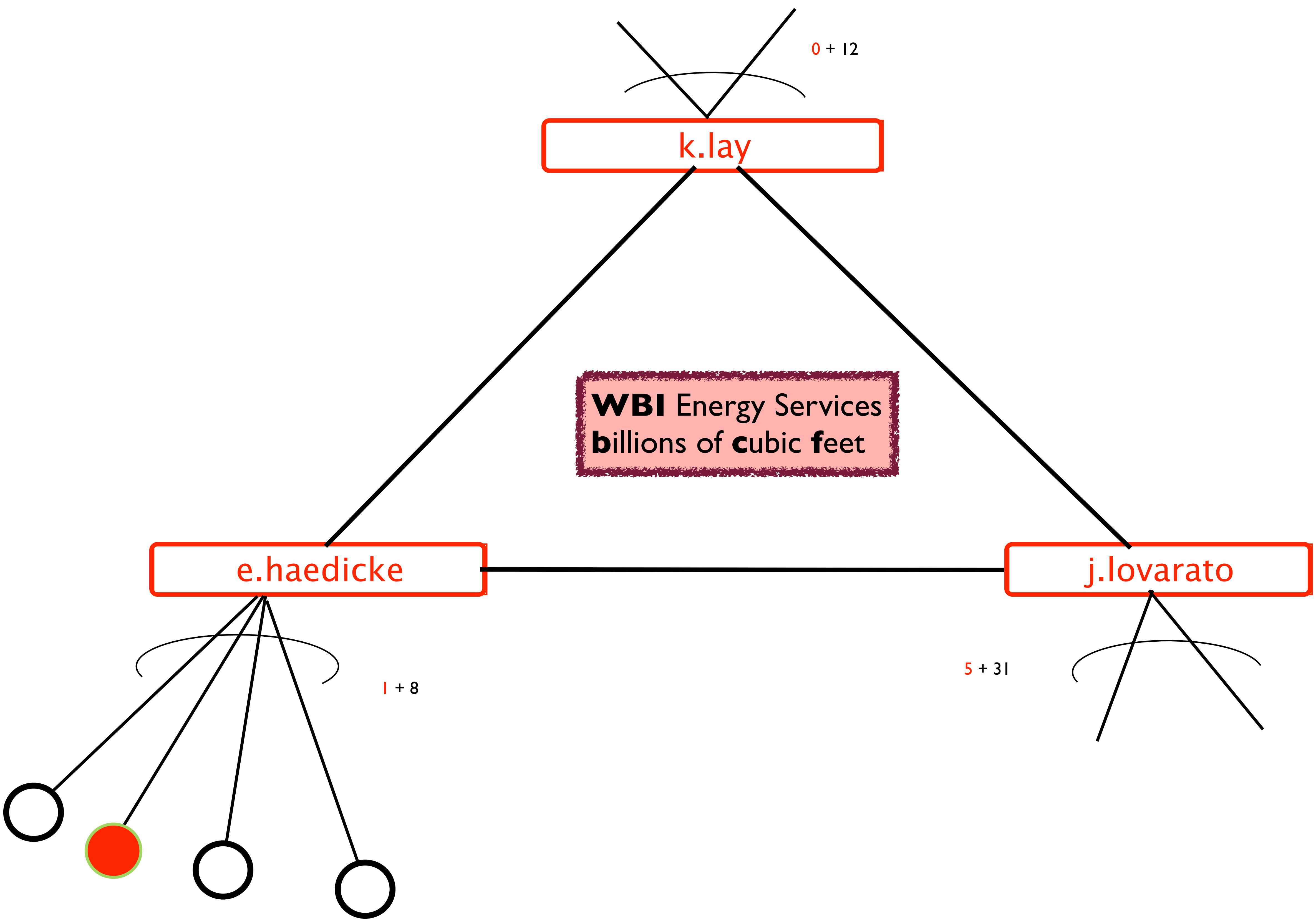

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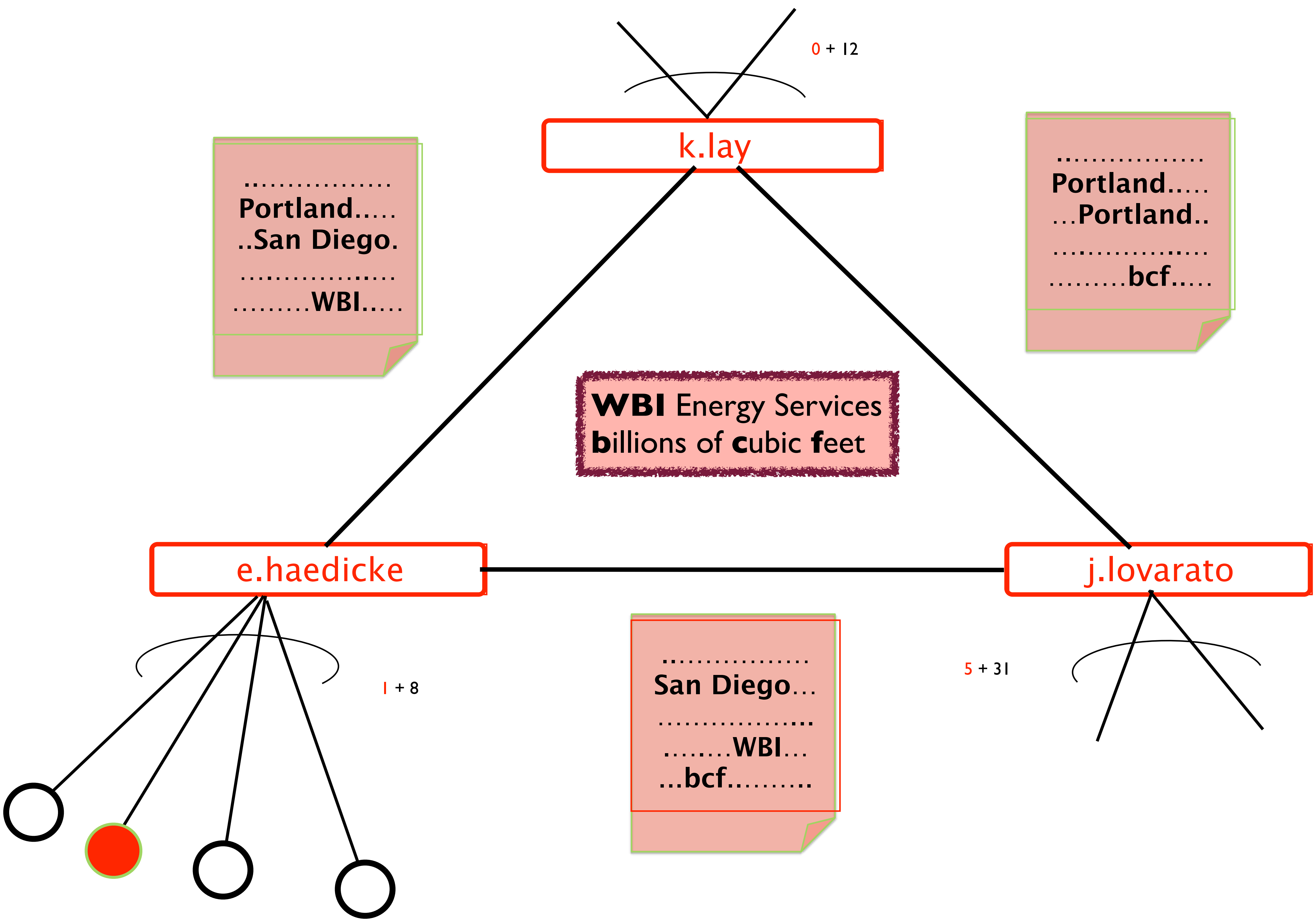

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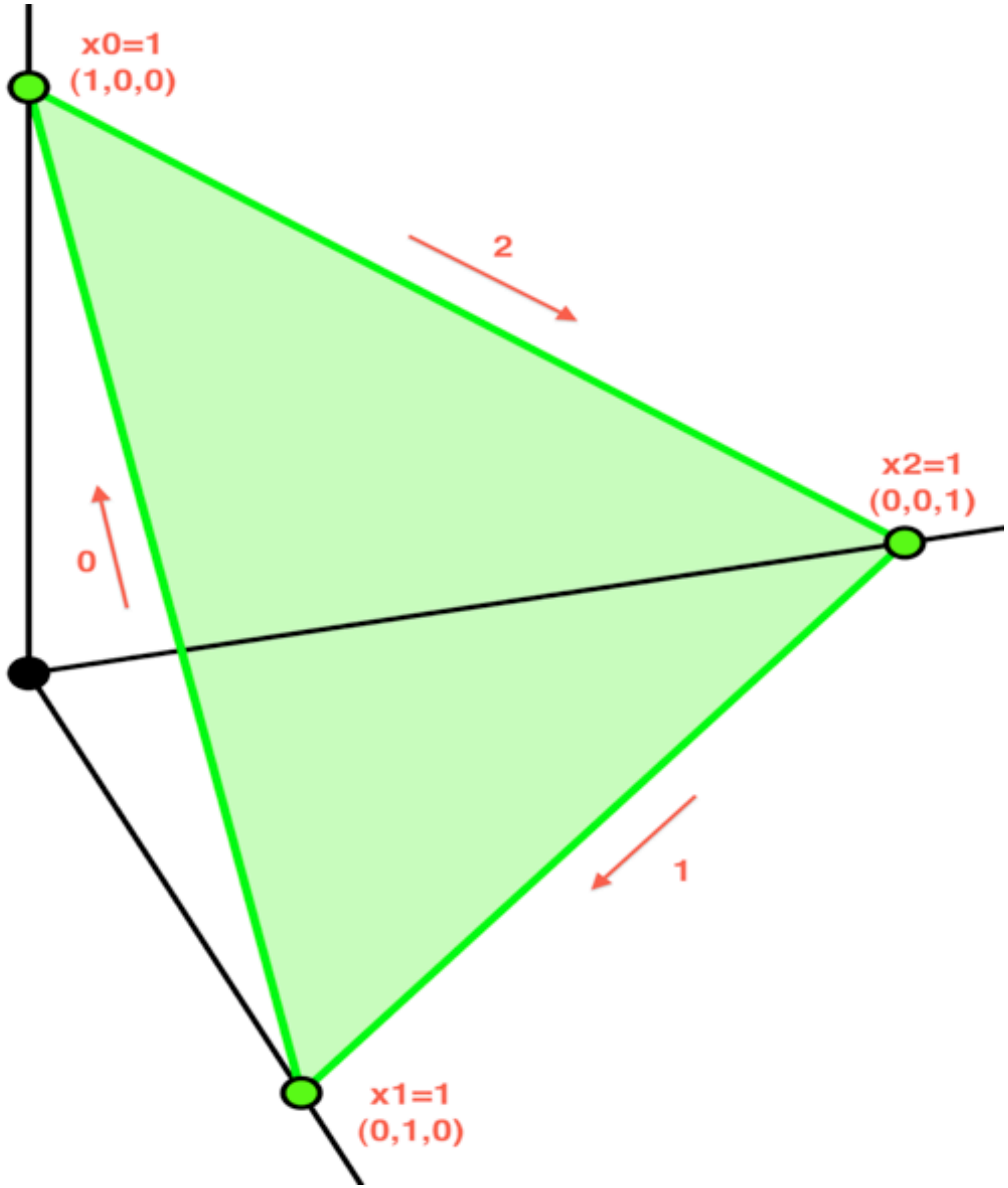
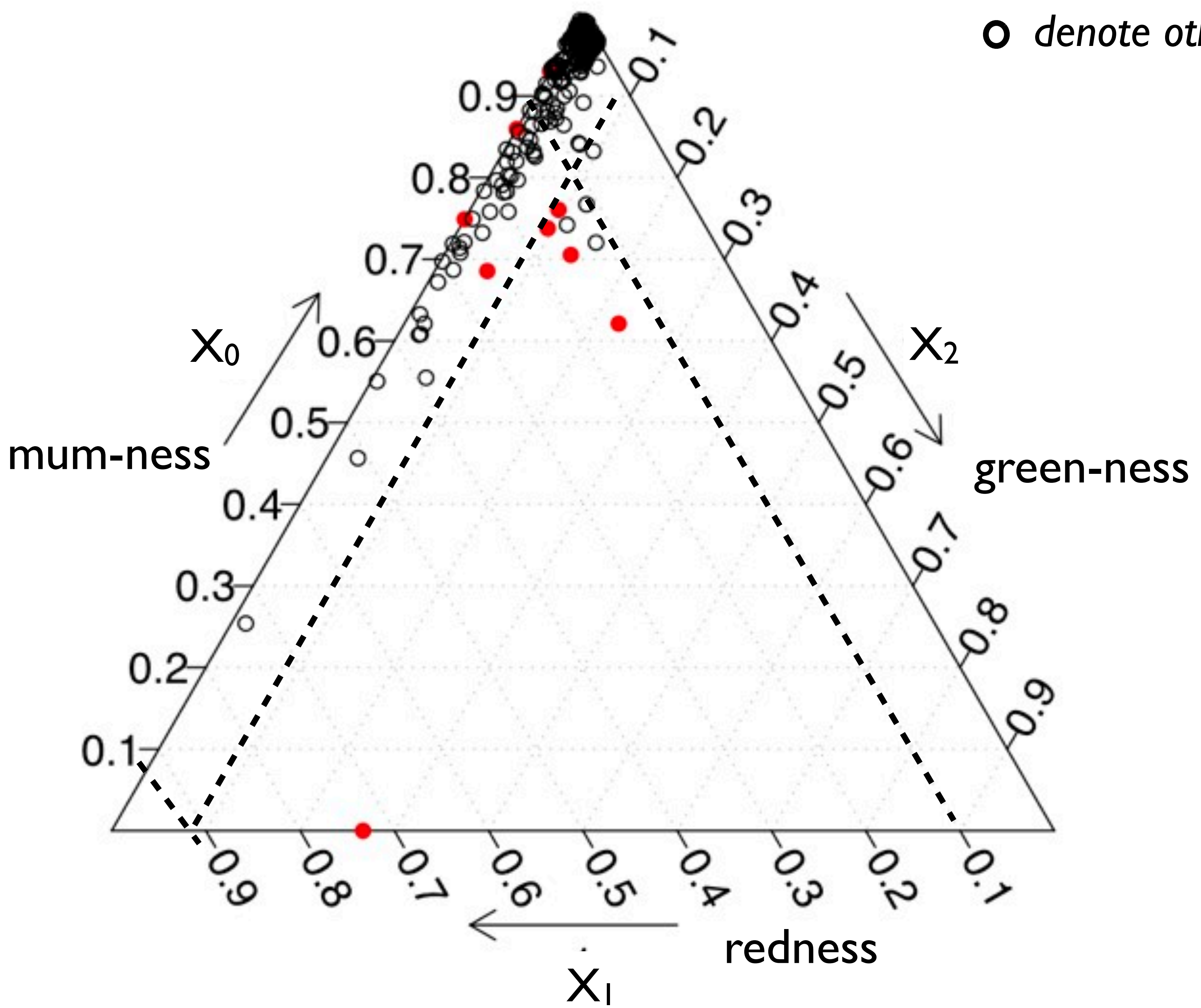
    - call this the 'greenness of the vertex'
  - $\mathbf{x_0} = 1 - x_1 - x_2$ = non-edginess = tendency of the vertex to stay mum

Latent Vertex Attributes live in the 2D simplex



x0 ~ mum-ness
x1 ~ redness
x2 ~ greenness

Distribution of 184 Latent Vertex Attributes



● *denote initial red vertices*

o *denote other vertices*

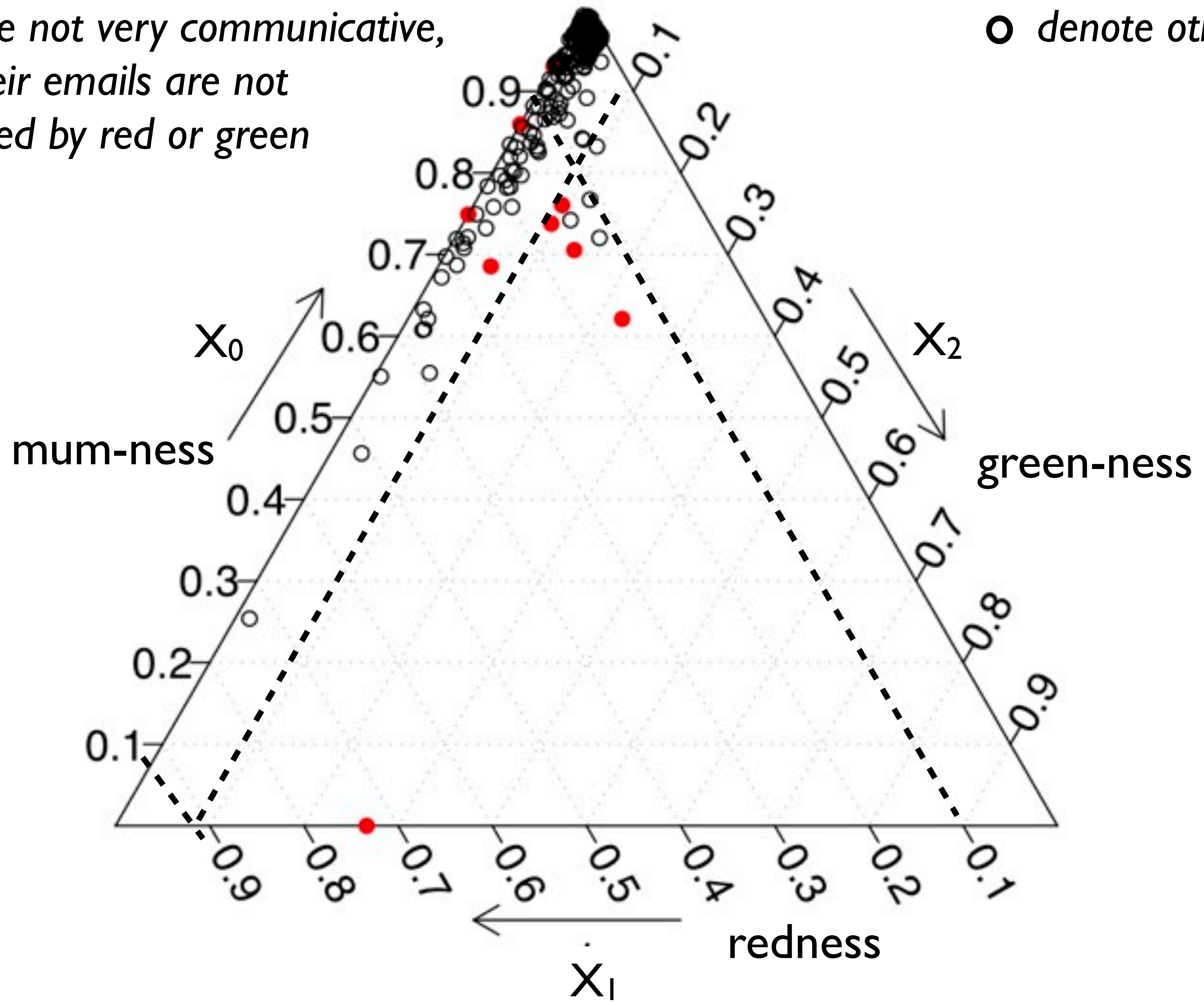
Distribution of 184 Latent Vertex Attributes

Sparse Communication Graph

most vertices are not very communicative, and their emails are not dominated by red or green

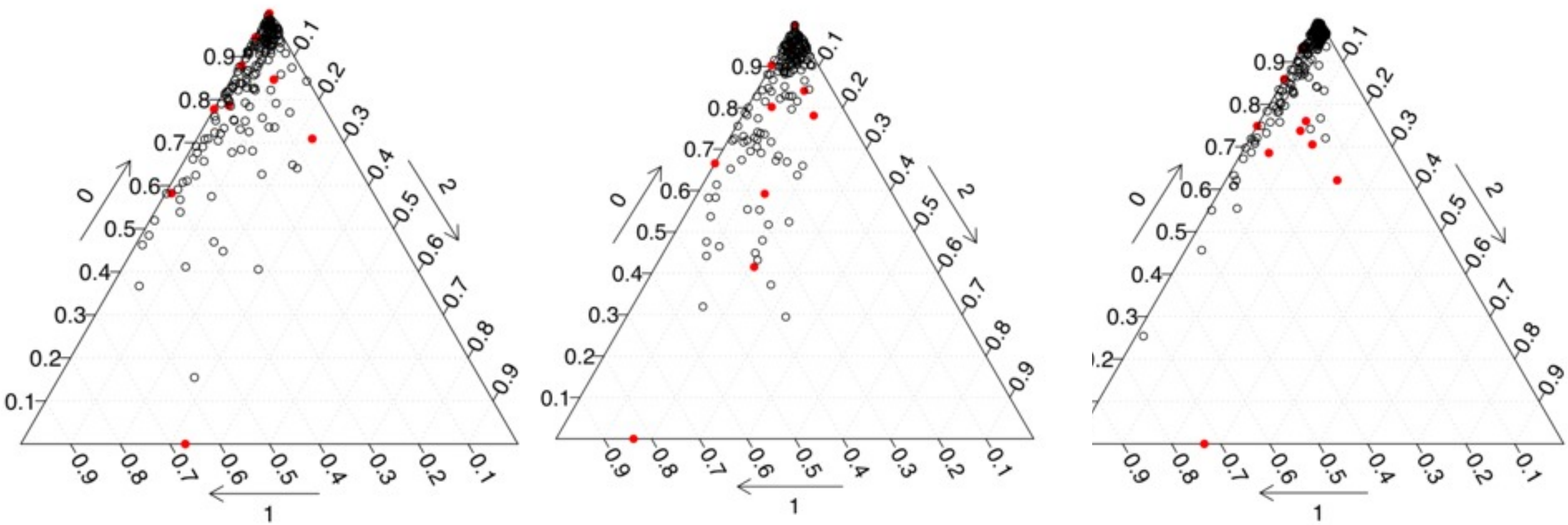
● *denote initial red vertices*

○ *denote other vertices*



Anomalous Chatter Group in Enron Time Series

Induced Egg



Egg?	p>0.99	p~ 0.7	**p < 0.01**
Time	Weeks 18-37	Weeks 38-57	Weeks 58-77

Conclusions

- New Methods for Fusion of Conte***x***t and Conte***n***t
- Pioneered at JHU Human Language Technology COE
- Theory, Algorithms and Experimental Evaluation
- Tasks
  - Stream Characterization
  - Vertex Nomination
  - Dyadic Priors
- Experimentally evaluated on
  - Enron email corpus
  - Switchboard speech corpus
  - other data

Some References

- ***Statistical Inference on Random Graphs: Fusion of Graph Features and Content,*** Grothendieck, Priebe, and Gorin, Computational Statistics and Data Analysis (2010)
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